International Journal of Management, Accounting and Economics
Vol. 9, No. 1, January, 2022
ISSN 2383-2126 (Online)

www.ijmae.com

Original research

The Effects of ICT and Technological Innovation on Environmental Quality: Evidence from Asian Developing Countries

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Abstract

ICT has been considered a crucial player in environmental quality in the present age of industrial revolution and technological advancement. This study, therefore, seeks to examine the effects of ICT on environmental quality including technological innovation in selected Asian developing countries. A panel data that spanned from 1990 to 2018 is utilized to pursue the objectives of this study by applying second-generation panel approaches. In the long run, an inverted U-shaped relationship between the ICT index and CO2 emission is found by FEM and FMOLS estimators, indicating that environmental pollution decreases after attaining a threshold level of ICT development in selected Asian developing countries. The study reveals that technological innovation has a negative and significant influence on reducing CO2 emission, leading to energy efficiency and diminishing the intensity of energy used by inventing environmentally friendly technologies. Besides, electricity consumption and economic growth have positive and significant effects on the environment however, a negative and significant effect is found in the case of trade openness. The interactive effect of ICT and economic growth decreases the level of pollution while the moderate effect of ICT and technological innovation worsens the environmental quality in sample countries. The findings reveal that the role of ICT and technological innovation in mitigating environmental degradation still needs improvement in sample countries. The use of environmentally friendly ICT products and more green technological innovation are needed to improve energy efficiency by providing more fiscal incentives and infrastructures and enforcing environmental laws and regulations in the sample countries.

Keywords: Environmental quality, ICT development, technological innovation, FEM, FMOLS, Asian Developing Countries

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Introduction

The increasing economic activities involving the emission of greenhouse gasses have contributed to global environmental degradation in recent times. As climate change is considered a major global challenge, shaping global discourse, measures to mitigate CO2 emissions are becoming paramount on the table of global policymakers. It is found that more than 90% of emissions were produced in Europe and the United States in 1900. But in the second half of the 20th century, a significant amount of carbon was released by the rest of the world particularly across Asia and particularly in China. Currently, China is considered Asia's and the world's 1st largest emitter of CO2, releasing nearly 10.29 billion tons in 2018. Following China, India become the 2nd highest emitter which emitted around 2.60 billion tons in 2018 (Ritchie & Roser, 2020). The other main contributors in Asia are Iran, Saudi Arabia, Turkey, Indonesia with 9.8 billion tones, 2.5 billion tons, 672 million tons, 635 million tons, 447 million tons, 489 million tons respectively in 2017. In the case of growing industrialization, economic diversification, and an increase in energy demand, it is predicted that the number of emissions will increase in the coming decades. To achieve these global goals to acquire environmental sustainability, a modern, automatic and digital production process is needed to promote ICT adoption and diffusion by raising lawful concern about their effect on the environment (Avom et al., 2020). Besides, technological innovation is considered as one of the significant contributors to abate global warming and ensure sustainable development (Fernández et al., 2018). Technological innovation can also be used to increase efficiency by reducing the production costs of renewable energy (Ellabban et al., 2014) along with the development of clean and low-carbon production processes for sustainable development (Ockwell et al., 2010). To overcome such kinds of climate change and energy crises, more proactive policies are needed to increase the levels of investment in modern and advanced technologies with environmentally friendly ICT products. Therefore, a comprehensive analysis is needed to examine whether ICT and technological innovation are better for improving environmental quality in selected Asian developing countries to set common environmental policies that reduce environmental pollution.

The research study intends to analyze the direct effects of ICT and technological innovation and the interactive effect of ICT and GDP and ICT and technological innovation on environmental quality in selected Asian developing countries by answering the following questions:

1. Are ICT development and technological innovation caused harmful effects on the environmental quality in selected Asian developing countries?

2. Does the degree of this effect depend on the level of economic growth and technical innovation? If yes, then what types of initiatives are needed to enhance environmental quality? And

3. Whether there exists an inverted U-shaped relationship between ICT and the environmental quality in selected countries?

The Environmental Kuznets Curve (EKC) framework of Grossman & Krueger, (1991) is used to accomplish the objectives of the study which indicates the inverted U-shaped relationship between per capita CO2 emissions with per capita GDP. To broaden the concept of the EKC, this study examines the relationship between the environment and ICT by assuming whether there exists an inverted U-shaped relationship between ICT and environmental quality (an initial development of ICT usage can lessen the level of CO2 emission).

The rest of the paper consists of different sections. **Section 2** discusses the related literature and the formation of hypotheses in the literature review. The data and model construction are discussed in data descriptions and model specifications in **Section 3 and Section 4** respectively. **Section 5** provides different econometric methods in the methodological framework. **Section 6** discusses the empirical results from the data in results and discussion. And **Section 7** provides the major conclusions and some policy implications from the findings in concluding remarks.

Literature Review

ICT and Environment

The impacts of ICT on environmental quality have been examined and different conclusions from different perspectives have been found. Some researchers argue that ICT improves environmental quality and helps to reduce pollutant emissions by adopting environmentally friendly technologies to replace the old energy-intensive production technologies. Accordingly, Park et al., (2018) found that ICT penetration reduces CO2 emissions while electricity consumption increases in selected 23 EU countries during 2001-2014. Lu, (2018) found that the use of ICT decreases the level of CO2 emission from 1993 to 2013 in selected 12 Asian countries. In addition, Danish, (2019) found that ICT mitigates the level of CO2 emissions in countries along Belt and Road in 59 countries from 1990 to 2016. Haseeb et al., (2019) found that the growth of both internet use and cell phone subscription decreased CO2 emissions in BRICS countries from 1994 to 2014. Furthermore, some other researchers recommend that IT-related products contribute to climate degradation by releasing a heavy amount of CO2 emissions. The development of ICT increases the demand for related products in which most of them are produced in an energy-intensive way resulting in increasing high energy consumption and pollution. Accordingly, Danish et al., (2018) found that the use of ICT worsens the environmental quality but the ICT development due to economic growth better the environment through decreasing CO2 emissions in emerging economies using the data from 1990 to 2015. Asongu et al., (2018) stated that ICT has positive effects on environmental degradation through CO2 emissions in 44 Sub-Saharan African countries from 2000 to 2012. Tsaurai and Chimbo, (2019) explored that ICT investments contributed to the reduction in air pollution in the emerging markets from 1994 to 2014. Arshad et al., (2020) analyzed that the use of ICT deteriorated the environment quality in the South and South-east Asian region from 1990 to 2014. Avom et al., (2020) found that ICT use measured by mobile phone and internet penetrations significantly worsens CO2 emissions in 21 Sub-Saharan African countries from 1996 to 2014. Raheem et al., (2020) also found that ICT development attributed to environmental degradation by increasing CO2 emissions in the G7

International Journal of Management, Accounting and Economics
Vol. 9, No. 1, January, 2022
ISSN 2383-2126 (Online)

www.ijmae.com

countries from 1990-to 2014. Some studies have been conducted on poor e-waste management which causes a burden on the environment (Widmer et al., 2005). Furthermore, Asia produced the highest amount of e-waste at 24.9 Mt from a total of 53.6 Mt of e-waste globally in 2019 in which only 11.7% of e-waste was formally collected and properly recycled (Forti, et al., 2020). This generation of e-waste threatens the environment and human health and can cause long-term effects if not managed in an environmentally sound manner (Liu et al., 2006). Moreover, it is also argued that ICT development causes both positive and negative effects on the environment. Accordingly, Higón et al., (2017) examined whether an inverted U-shaped relationship exists between ICT and CO2 emissions for the global aspect and sub-panels of developed and developing countries. The results explored that developed countries have reached the initial level of ICT development but developing countries need to improve further. Similarly, Faisal et al., (2020) also explored an inverted U-shaped relationship between ICT and CO2 emission in the fast-emerging countries from 1993 to 2014. Majeed, (2018) also found that ICT contributed to decreasing in CO2 in developed economies but not in developing economies in 132 developed and developing economies over the period 1980-2016. Besides, Zhang et al., (2019) explored that ICT reduces CO2 emissions in high- and middle-income countries but not in low-income countries by using panel data from 1990 to 2015. Khan et al., (2020) also found that the ICT index contributed to decreasing CO2 emission in 91 sample countries and developed countries but negative and significant impact on developing countries from 1990 to 2017. But any significant association between ICT and CO2 emissions was not found for Tunisia from 1975 to 2014 (Amri, 2018).

Technological Innovation and Environment

Technological development and innovation address the challenges of climate change and achieve sustainable development have acquired an important role in the economic literature in recent years. Several researchers investigated the relationship between environmental quality and technological development and innovation and found a positive effect on the environment. According to the findings of Fernández et al., (2018) innovation improves environmental quality in US and European countries but on the contrary, it harms environmental quality in china from 1990 to 2013. Kahouli, (2018) found a negative and unidirectional relationship between total R&D investments and CO2 emissions in the Mediterranean countries for the period of 1990-2016. Hashmi & Alam, (2019) also expressed that environmentally friendly patent reduces carbon emissions of OECD countries during the period 1999-2014. Ganda, (2019) found a positive and significant effect between triadic patent families, but negative and significant effects are found between R&D investment and CO2 emissions in OECD countries from the period of 2000 to 2014. Demir et al., (2020) found an inverted U-shape curve between technological innovation and environmental quality in Turkey. Dauda et al., (2019) revealed that technological innovation enhances the environment quality in G7 countries but increases CO2 emissions in MENA and the BRICS countries from 1990 to 2016. Likewise, Ibrahiem, (2020) disclosed that technological innovation and alternative energy resources improve environmental quality in Egypt over the period from 1971 to 2014. On the other hand, some other studies found an adverse effect of technological developments and innovation on environmental quality. Accordingly, Churchill et al., (2019) explored those R&D activities significantly

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ISSN 2383-2126 (Online)

www.ijmae.com

enhancing the environmental quality through CO2 emissions during the period from 1870 to 2014 in G7 countries. Furthermore, Huang et al., (2020) found that R&D can reduce carbon intensity and that carbon intensity is affected by R&D activities depending on its different stages and actors in China from 2000 to 2016. Youssef, (2020) analyzed that non-resident patents improve the environmental quality while resident patents increase carbon emissions in the USA from 1980 to 2016. Sinha et al., (2020) also found technological advancements degraded the environmental quality for the N-11 countries from 1990 to 2017. Besides, a positive but insignificant effect of innovation on environmental quality was confirmed by the findings of Cheng et al., (2019) who examined the association between economic growth, clean energy, patent applications, and carbon emissions from 2000 to 2013 in OECD member countries. Likewise, Usman & Hammar, (2021) also examined that technological innovation significantly worsen the environmental quality in APEC countries from 1990 to 2017. Omri & Hadj, (2020) found revealed that technological innovation has decreasing effects on the level of CO2 emissions in 23 emerging economies from 1996 to 2014. In the context of these contradictory findings, it is important to carry out new research on the effect of ICT penetration on environmental quality by taking technological innovation in selected Asian developing countries.

Hypotheses formation

Considering the above discussions on the relationship between ICT, economic growth, technological innovation, and CO2 emissions, the proposed hypotheses are as follows:

i. ICT penetration and technological innovation increase CO2 emissions in selected Asian developing countries.

ii. Technological innovation and economic growth complement ICT to reduce CO2 emissions in selected Asian developing countries.

Data Descriptions

The current study aims to explore the effects of ICT and technological innovation on environmental quality in 34 selected Asian developing countries alphabetically Armenia, Azerbaijan, Bahrain, Bangladesh, Brunei, Cambodia, China, Georgia, India, Indonesia, Iran, Iraq, Jordan, Kazakhstan, Kyrgyzstan, Kuwait, Lebanon, Malaysia, Mongolia, Myanmar, Nepal, Oman, Pakistan, Philippines, Qatar, Saudi Arabia, Sri Lanka, Tajikistan, Thailand, Turkmenistan, Turkey, the United Arab Emirates, Uzbekistan, Viet Nam over the period of 1990 to 2018. The detailed variables definitions and data sources are provided in Table 1. The summary statistics of the variables are summarized in Table 2.

Table 1. The Description of the Variable

Variables Name	Unit of Measurement	Data Source
1. Carbon emission	Metric tons per capita	WDI (2020)
2. ICT Index		
i. Mobile subscriptions	Per 100 people	WDI (2020)
ii. Internet users	% of the population	WDI (2020)
iii. Broadband subscriptions	Per 100 people	WDI (2020)
iv. Telephone subscriptions	Per 100 people	WDI (2020)
3. Technological Innovation Index		
i. Trademark	Total trademark application	WDI (2020)
ii. Patent	Total patent application	WIPO (2020)
iii. Technical cooperation grants	BoP, current US$	WDI (2020)
4. Economic growth	GDP Per capita (constant 2010 US$)	WDI (2020)
5. Electricity consumption	kWh per capita	WDI (2020)
6. Trade openness	The sum of export & import (% of GDP)	WDI (2020)

WDI is World Bank Indicator and WIPO is World Intellectual Property Organization

Table 2. Summary Statistics of the Variables

Variables	Observations	Mean	Std. Dev.	Min.	Max.
LnCO2	986	1.5263	0.9965	0.0000	3.8857
LnICT	986	0.6141	0.3573	0.4071	2.1130
LnTI	986	0.6054	0.3901	0.1257	2.0857
LnELE	986	6.1788	2.8808	0.0000	9.9826
LnY	986	7.9940	1.7491	0.0000	11.1517
LnTO	986	4.0702	1.1350	0.0000	5.4000

Model Specifications

This study investigates the direct influence of ICT and technological innovation on the environmental quality including the moderate effects between ICT and economic growth with technological innovation, by following the study of Avom et al., (2020);

Faisal et al., (2020) and Danish et al., (2018). Accordingly, the model with the interaction term of ICT*Y and ICT*TI is as follows:

$$lnCO2_{it}=\alpha_0+\alpha_1lnICT_{it}+\alpha_2lnICT^2_{it}+\alpha_3lnTI_{it}+\alpha_4lnELE_{it}+\alpha_5lnY_{it}+\alpha_6lnTO_{it}+\epsilon_{it} \quad (1)$$

$$lnCO2_{it}=\beta_0+\beta_1lnICT_{it}+\beta_2lnICT^2_{it}+\beta_3lnTI_{it}+\beta_4lnELE_{it}+\beta_5lnY_{it}+\beta_6lnTO_{it+}\beta_7ln(ICT^*Y)_{it}+\epsilon_{it} \quad (2)$$

$$lnCO2_{it}=\gamma_0+\gamma_1lnICT_{it}+\gamma_2lnICT^2_{it}+\gamma_3lnTI_{it}+\gamma_4lnELE_{it}+\gamma_5lnY_{it}+\gamma_6lnTO_{it+}\gamma_7ln(ICT^*TI)_{it}+\epsilon_{it} \quad (3)$$

where, CO2 is the amount of carbon emission, the proxy of measuring environmental quality, ICT and ICT^2 show ICT index measured by different proxies and its square term respectively, TI is the technological innovation index, Y shows per capita GDP, ELE is the electricity consumption and TO shows trade openness. The subscripts t, i, and μ show the period, cross-sections, and error terms respectively. The four sub-components of ICT such as internet users, mobile subscriptions, telephone subscriptions, and fixed broadband subscriptions are used to form an ICT index which is consistent with recent literature (Higón et al., 2017 and Khan et al., 2020). For measuring technological innovation, this study uses the number of patent applications, total trademark applications, and technical cooperation grants to construct the technological innovation index by following the study of Sinha et al., (2020) and Usman & Hammar, (2021). The principal component analysis (PCA) is applied to construct both indexes to check multicollinearity issues (Lu, 2018). As every nation has different economic growth, R&D expenditure, single indicator of R&D and ICT components might not represent the actual condition of technological innovations and ICT development in the selected countries. All variables are converted into a logarithmic form to minimize the problem of data sharpness and heteroscedasticity (Danish et al., 2018). The effects of ICT on the environment can be positive or negative, or insignificant (Haseeb et al., 2019). If the coefficient of ICT and its square term is positive and negative respectively, it would support the hypothesis that high-level ICT penetration is associated with a decrease in CO2 emissions. A negative affiliation between technological innovation and CO2 emissions is expected in these selected countries (Omri & Hadj, 2020). The expected signs of electricity consumption and economic growth are positive and negative for trade openness. Moreover, the moderate effect of ICT*Y is examined to find out whether growing economic activities along with the development of ICT products deteriorate the environment. Likewise, the interaction effect of ICT*TI on the environment is also investigated to check whether the combined effect of these two can improve the environment with the advancement of technological innovation and ICT. So, the sign of ICT*Y and ICT*TI is expected to be negative.

Methodological Framework

The current study applies the following advanced second-generation econometric techniques by pursuing the study of Arshad et al., (2020); Faisal et al., (2020) and Khan et al., (2020):

Cross-sectional dependency test

To check the cross-sectional dependence (CD) in variables, this study utilizes three CD tests (a) Pesaran et al., (2008) developed LM test, (b) Baltagi et al., (2012) proposed bias-corrected scaled LM test, and (c) finally CD test established by Pesaran, (2004) as the cross-section is higher than period (N>T). The null hypothesis of this test supposes that there is no CD in the panel data. To address the CD problem in the panel data is needed otherwise biased value of the unit root and the cointegration analysis may be found.

Slope homogeneity test

The slope heterogeneity test by Pesaran and Yamagata, (2008) is used to reveal the slope homogeneity between the cross-sections which is preferable to other conventional homogeneity measures as they do not permit for the cross-sectional dependency (Atasoy, 2017). Thus, ambiguous results can be found if there exist homogeneity constraints in the model (Alam et al., 2018). The model of this test is expressed as:

$$\tilde{\Delta}_{SH} = (N)^{1/2}(2K)^{-1/2}\left(\frac{1}{N}\tilde{S} - k\right) \quad (4)$$

$$\tilde{\Delta}_{ASH} = (N)^{1/2}\left(\frac{2k(T-k-1)}{T+1}\right)^{-1/2}\left(\frac{1}{N}\tilde{S} - k\right) \quad (5)$$

Where $\tilde{\Delta}_{SH}$ and $\tilde{\Delta}_{ASH}$ show the delta tilde and the adjusted delta tilde respectively.

Panel unit root tests

The second-generation unit roots test, the CADF, and CIPS tests developed by Pesaran, (2007) are to be applied. Both tests can check the Cross-sectional dependency and heterogeneity with more consistent results. The dynamic linear heterogeneous model with N cross-section of countries can be written in Eq. 6 as follows:

$$\Delta y_{it} = \alpha_i + b_i y_{i;t-1} + \beta_i \bar{y}_{t-1} + \sum_{j=0}^{k} \gamma_{ij} \Delta \bar{y}_{t-j} + \sum_{j=1}^{k} \delta_{ij} \Delta y_{i,t-j} + \varepsilon_{it} \quad (6)$$

where y_{t-1} is the lagged level of cross-sectional averages, $\bar{Y}_{t-j}$ is the first order of integration for every cross-section. CIPS unit root test is found by obtaining t-value from CADF which is described as follow in Eq. 7:

$$CIPS = N^{-1} \sum_{i=1}^{N} CADF \quad (7)$$

Panel cointegration test

To analyze the long-run association among the concerned variables, the study applies the Westerlund panel cointegration test (Westerlund, 2007) to check both CD and heterogeneity issues. In this test, there are two group statistics (G_t and G_a) and two panel statistics (P_t and P_a). The null hypothesis considers that there is no cointegration for at least one cross-section for the G_t, and all cross-sections for P_t. The error correction

based cointegration test considers that all variables are integrated of I(1) and discussed below in Eq. 8:

$$\Delta y_{it} = \delta'_i d_i + \alpha_i (y_{i,t-1} - \beta'_i x_{i,t-1}) + \sum_{j=1}^{p_i} \alpha_{ij} \Delta y_{i,t-j} + \sum_{j=-q_i}^{p_i} \gamma_{ij} \Delta x_{i,t-j} + u_{it} \quad (8)$$

where d_t is the deterministic components and p_i and q_i are the lag lengths and lead orders which vary across individual cross-sections. The two group-mean test statistics G_t and G_a and the two-panel test statistics P_t and P_a are shown as follows:

$$G_t = N^{-1} \sum_{i=1}^{N} \frac{\hat{\alpha}_i}{SE(\hat{\alpha}_i)} \quad (9)$$

$$G_a = N^{-1} \sum_{i=1}^{N} \frac{T\hat{\alpha}_i}{\hat{\alpha}_i(1)} \quad (10)$$

$$P_t = \frac{\hat{\alpha}_i}{SE(\hat{\alpha}_i)} \quad (11)$$

$$P_a = T(\hat{\alpha}) \quad (12)$$

Where, $\hat{\alpha}_i$ describes the adjustment speed/short to long-run equilibrium.

Long-run estimations

The fixed effects model (FEM) and fully modified ordinary least square (FMOLS) methods are used to examine the long-run relationships after finding out the cointegration relationship in the present study. The FEM estimates the influence of variables that changes over time. It deals with the differences in the intercept so that intercept changes for each cross-section but the slope remains the same and introduces fixed dummies to capture the differences among countries The Hausman test (1978) is used to determine whether the fixed effects or the random effects model should be accepted for the panel regression model. The null and alternative hypotheses of this test are given below:

H_0: Random Effects model is the suitable estimator or $(\omega_i, X_{it}) = 0$ and

H_1: Fixed Effects model is the suitable estimator or $(\omega_i, X_{it}) \neq 0$.

If the p-value of the chi-square statistic is less than 0.05 we reject the null hypothesis and conclude that the is the most appropriate than Random Effects Model.

In the presence of cross-sectional dependency, the FEM estimator is consistent but not efficient. So, for the robust results, the FMOLS estimator proposed by Pedroni, (2001) is also used which can check the possible effects of bias, endogeneity, and serial correlation in the error term which can affect the coefficient of the panel data (Bhattacharya et al., 2017). FMOLS shows the non-parametric approach estimates of the regression analysis. The functional form of FMOLS estimates is given in Eq. 13 as follows:

$$X_{it} = \alpha_i + \beta Y_{it} + \varepsilon_{it} \quad (13)$$

ISSN 2383-2126 (Online)

where Y and X are the vector of cointegration. The model is described below:

$$\widehat{\alpha}^*_{GFM} = N^{-1} \sum_{i=1}^{N} \widehat{\alpha}^*_{FM,n} \quad (14)$$

$\widehat{\alpha}^*_{GFM,n}$ shows the FMOLS regressions parameter applied on cross-sections n and the related t-statistic coefficient shown in Eq. 15 as follows:

$$t_{\widehat{\alpha}^*_{GFM}} = N^{-1/2} \sum_{i=1}^{N} t_{\widehat{\alpha}^*_{FM,n}} \quad (15)$$

Results and discussions

The results of the pairwise correlation of the variables are shown in Table 3 to check the multicollinearity issue and it found that LnCO2 is weakly correlated with LnTI, LnTO, LnICT, LnY, and LnELE. The results indicate that there is no multicollinearity among the variable as all values are below 0.80% (Gujarati, 2004).

Table 3. Results of Pairwise Correlations

	LnCO2	LnICT	LnTI	LnELE	LnY	LnTO
LnCO2	1					
LnICT	0.3075***	1				
LnTI	-0.5116***	-0.0551*	1			
LnELE	0.3717***	-0.3140***	0.2051***	1		
LnY	0.6191***	0.3584***	-0.2450***	0.2119***	1	
LnTO	0.1517***	0.2043***	-0.0054	0.1025***	0.2604***	1

***, **, and * represent the significance levels at 1%, 5%, and 10%, respectively.

Moreover, and results of the variance inflation factor (VIF) tests are also shown in Table 4 for checking multicollinearity problems. Here, the average VIF value is less than 5 which indicates that there is no threat of multicollinearity in the models (Khan et al., 2020).

Table 4. Results of Multicollinearity Tests

Variables	VIF	1/VIF
LnICT	1.44	0.69
LnY	1.40	0.71
LnELE	1.34	0.75
LnTI	1.10	0.91
LnTO	1.11	0.90
Mean VIF	1.28	

International Journal of Management, Accounting and Economics
Vol. xx, No. xx, xxxxx, 202x
ISSN 2383-2126 (Online)

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The results of three different cross-sectional dependency approaches (CD), namely Pesaran scaled LM, and bias-corrected scaled LM tests and Pesaran CD are shown in Table 5. According to these cross-sectional dependency tests, the null hypothesis of no CD between countries is rejected at a 1% level of significance which confirms that disturbance in one country affects the other country.

Table 5. Cross-Section Dependence Test Results

Variables	Pesaran scaled	Bias-corrected scaled	Pesaran CD
LnCO2	165.655***	165.0478***	22.04307***
LnICT	323.5781***	322.9709***	104.4728***
LnTI	91.2947***	90.6876***	6.8088***
LnELE	409.2897***	408.6825***	118.3475***
LnY	254.6629***	254.0558***	67.8996***
LnTO	68.2089***	67.6018***	13.3584***

***, **, and * represent the significance levels at 1%, 5%, and 10%, respectively.
.

The results of the slope heterogeneity test are shown in Table 6. It confirms the existence of slope heterogeneity in the model which informs that any socioeconomic structural connections of one country cannot generally be moved by the other countries (Bao & Xu, 2019).

Table 6. Slope Homogeneity Test Results

Test-Statistics	Value	P-value
$\tilde{\Delta}$	30.4810 ***	0.000
$\tilde{\Delta}$ adjusted	34.9960***	0.000

***, **, and * represent the significance levels at 1%, 5%, and 10%, respectively

After checking the cross-sectional dependency in the panel data, the results of the CIPS and CADF unit root test are shown in Table 7. The CIPS results indicate that LnTI and LnTO are stationary at both levels and their first difference, and LnCO2, LnICT, LnY, and LnELE are stationary at their first difference, confirming the rejection of the null hypothesis of no stationary in the variables. According to the results CADF unit root test, LnCO2, LnTI and LnTO are stationary are at both levels and their first difference, and all other variables are stationary at their first difference. Thus, it is affirmed from these unit root tests that all variables are stationary and suitable to check long-run cointegration among variables.

Table 7. Panel Unit Root Test Results

Variables	CIPS		CADF	
	At level	1st difference	At level	1st difference
LnCO2	1.0706	-19.7321***	96.6787***	474.3130***
LnICT	129.9390	-2.3930***	75.7087	173.4390***
LnTI	137.9740***	689.1240***	139.6760***	766.8290
LnELE	5.4598	-21.8569***	20.7602	531.8410***
LnY	5.5363	-15.3885***	53.7817	356.2460***
LnTO	-6.5251***	-27.2033***	317.3200***	555.1250***

***, **, and * represent the significance levels at 1%, 5%, and 10%, respectively.

The results of the Westerlund cointegration test are shown in Table 8 in which the p values reject the null hypothesis of no cointegration. Moreover, the bootstrap approach of Westerlund is also used to determine the long-run relationship in the presence of cross-sectional dependency. The robust p values are found based on 10 bootstrap replications with constant, zero lag and zero lead using 34 series and 5 covariates. The results of robust p values of the bootstrap cointegration test also confirm the cointegration among the selected variables which is in line with Usman & Hammar, (2021) and Arshad et al., (2020). Because of the existence of heterogeneity and cross-sectional dependency in the series, this study applies the FMOLS and FEM which are more reliable in producing the long-run estimator.

Table 8. Westerlund Bootstrap Cointegration Test Results

Test	Statistics	Z-value	P-value	Robust P-value
Gt	-2.962***	-1.931	0.027	0.000
Ga	-11.448***	2.495	0.994	0.000
Pt	-18.975***	-4.754	0.000	0.000
Pa	-11.814***	-0.349	0.363	0.000

***, **, and * represent the significance levels at 1%, 5%, and 10%, respectively.

The results of the FEM and FMOLS are shown in Table 9 for Models 1, 2, and 3. According to the result of the Hausman test, it is found that the FEM is more applicable than REM as the p-value of the chi-square statistic is 0.00 which is less than 0.05. The long-run coefficient of the ICT index is positive and significant, and the ICT index square is negative and significant which supports the presence of an inverted U-shaped relationship between ICT and CO2 emissions.

ISSN 2383-2126 (Online)

Table 9. Results of Long-Run Elasticity Estimates

Variable	FEM			FMOLS		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
LnICT	0.6076***	1.7106 ***	0.2744**	0.6584***	1.9720***	0.3160*
$LnICT^2$	-0.2147***	-0.1113*	-0.2051***	-0.2473***	-0.1228**	-0.2367***
LnTI	-0.1736***	-0.2099***	-0.5064***	-0.1425*	-0.1731***	-0.5198***
LnELE	0.0149***	0.0156***	0.0118***	0.0131**	0.0152***	0.0091*
LnY	0.0838***	0.1471***	0.0845***	0.0783***	0.1645***	0.0786***
LnTO	-0.0477***	-0.0399***	-0.0371***	-0.0502***	-0.0434***	-0.0345**
LnICT*Y		-0.1424***			-0.1684***	
LnICT*TI			0.5418***			0.5461***
Constant	0.7985***	0.2801**	0.9733***			
R^2	0.9502	0.9519	0.9553	0.9536	0.9555	0.9583
Adjusted R^2	0.9481	0.9498	0.9534	0.9516	0.9535	0.9564
F statistic (p-value)	462.8241 (0.0000)	478.0153 (0.0000)	510.9901 (0.0000)			
Hausman test (p-value)	83.72*** (0.0000)	115.40*** (0.0000)	82.54*** (0.0000)			

FEM=Fixed effect model, FMOLS=Panel fully modified least squares; ICT and ICT^2 denote Information and communication technology and its square term respectively; TI measures technological innovation; ELE represents electricity consumption; Y denotes GDP per capita, TO measures Trade openness; LnICT*Y depicts the interaction of ICT and GDP per capita and LnICT*TI represents the interaction of ICT and technological innovation

***, **, and * represent the significance levels at 1%, 5%, and 10%, respectively.

It indicates that after reaching a threshold level, internet users improved the environmental quality by reducing pollution with the use of environmentally friendly ICT equipment. This could intensify energy efficiency and encourage effective use of the internet (Faisal et al., 2020). Moreover, aggregation of output, input, and technology effects of ICT overcomes the scale effect of ICT, then this negative effect of ICT is observed for CO2 emissions (Danish, 2019; Higón et al., 2017) which also indicates technological improvement and efficient use of energy (Khan et al., 2020). These results are similar to the study of Higón et al., (2017) and Faisal et al., (2020) and contrasted to Avom et al., (2020); Danish et al., (2018). The long-run elasticity of technological innovation is significant and negative, indicating that technological innovation can effectively improve the environmental quality in these selected countries by inventing environmentally friendly technologies. This may also happen because technological innovation leads to energy efficiency and diminishes the intensity of energy use, which, in turn, reduces CO2 emissions (Sohag et al., 2015) but needs time to improve further. These findings are similar to those found by Fernández et al., (2018); Omri & Hadj, (2020); and inconsistent with Churchill et al., (2019); Sinha et al.,

(2020). The long-run coefficient of electricity consumption is positive and significant indicating that an increase in electricity consumption by internet users increases CO2 emissions. This could be explained by the high and the inefficient use of fossil fuels used to produce eccentricity in these sample countries. Moreover, the developing countries are involved in ancient production processes with more energy consumption which causes deprivation of the environment (Khan et al., 2020). The finding is parallel to Salahuddin et al., (2018); Faisal et al., (2020) and inconsistent with Dogan & Seker, (2016) and Haseeb et al., (2019). The long-run coefficient of GDP per capita is positive and significant which can be explained by the scale effect. A larger scale of economic activities needs more energy and produces higher levels of emissions that negatively affect the environment Dinda, (2004). Moreover, the growth of the industrial sector leads to the use of more fossil fuels and increases the level of CO2 emissions (Sohag et al., 2017). The findings are in parallel to the study of Lu, (2018); Danish et al., (2018) and inconsistent with Faisal et al., (2020); Park et al., (2018). The long-run coefficient of trade has negative with a significant effect on CO2 emissions. This finding is related to the factor endowment theory which predicts that the effect of trade openness on environmental quality depends on the capital-labor intensity in countries. As developing countries are well-endowed with natural resources, the labor will tend to specialize in the production and export of fewer dirty goods Avom et al., (2020). Furthermore, the developing countries mainly export capital-intensive goods from the developed countries (Suri & Chapman, 1998) and free trade decreases environmental degradation in the developing countries. The result is similar to the findings of studies by Arshad et al., (2020); Faisal et al., (2020) and inconsistent with Omri & Hadj, (2020) and Tsaurai & Chimbo, (2019). From Model 2, the interaction effect of economic growth and ICT is negative and significant which implies that the promotion of ICT due to economic growth enhances the environment through decreasing CO2 emission Danish et al., (2018) and Tsaurai & Chimbo, (2019). Moreover, in Model 3, the positive and significant impact of the interaction term of ICT and TI is found which implies that the advancement of technological innovation in the ICT sector increases the level of CO2 emission. The excessive use of ICT can consume higher electricity and it is challenging to reduce its consumption in these countries. However, the contribution of ICT in mitigating environmental degradation still needs improvement to make it environmentally friendly (Faisal et al., 2020). Furthermore, this degradation may be justified because technological innovations are based on the conventional technologies progression which encourages the conventional sources of energy utilization (Haseeb et al., 2019). Moreover, most of the inventors strictly protect their innovation ideas sharing to others (Raiser et al., 2017). So, progressive and green technologies are needed to ensure sustainable development in the ICT sector in these selected countries. These reported results are robust and reliable as second-generation unit root tests, cointegration tests, and long-run estimators are employed. Moreover, the robustness of the models is confirmed by the results of FEM and FMOLS.

Concluding Remarks

The study is designed to investigate the effects of ICT and technological innovation on environmental quality in terms of CO2 in selected Asian developing countries covering the period of 1990 to 2018. To report the actual condition of CT development along with the technological progression and innovations in the sample countries, the

ICT index and the technological innovation index are constructed. The second-generation panel approaches have been used to check out the issue of CD and heterogeneity. The existence of the EKC is found in the presence of ICT by the FEM and FMOLS indicating that it would be possible to enhance the environmental quality in the latter stages of the ICT development. However, technological innovation has a negative and significant influence on CO2 emission, leading to energy efficiency and diminishing the intensity of energy used by inventing environmentally friendly technologies. Moreover, electricity consumption and economic growth worsen the environmental quality and the opposite result is found for trade openness in sample countries. Moreover, ICT due to the development of economic growth decreases the level of pollution and the interaction between ICT and technological innovation harms the environmental quality by accelerating the level of pollution in these selected countries. For this reason, the role of ICT in mitigating environmental degradation still needs advancement to make it environmentally friendly in these developing countries. Thus, technological innovation for electricity and industrial production is needed to encourage the utilization of renewable energy sources and environmentally friendly ICT products and discourage the inefficient use of ICT as e-waste. To mitigate the adverse effects of ICT on environmental quality, effective policies should be designed to improve energy efficiency with renewable energy and provide more fiscal incentives for green technology development.

This study has some limitations which can be included in future research. The sample countries can be increased and some other variables can contribute to the existing literature by including institutional quality, globalization, natural resource in terms of ecological footprint, carbon footprint and help to suggest some policy implications in the selected Asian developing countries.

Acknowledgement

The author would like to thank Prof. Qunzhi She, School of Economics, Zhongnan University of Economics and Law, Wuhan, China for her valuable suggestions during the preparation of the manuscript. I would also like to thank the editor and two anonymous reviewers for their helpful and detailed comments. The usual disclaimers apply, and views are the sole responsibility of the authors.

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HOW TO CITE THIS ARTICLE

Tahsin, J. (2022). The Effects of ICT and Technological Innovation on Environmental Quality: Evidence from Asian Developing Countries. *International Journal of Management, Accounting and Economics*, 9(1), 14-33.

DOI: 10.5281/zenodo.6479344

URL: https://www.ijmae.com/article_147192.html